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(54) Multifunction control of a prosthetic limb using syntactic analysis of the dynamic myoelectric signal patterns associated with the onset of muscle contraction.

(57) A myoelectric control system for use with artificial limbs comprising means adapted to operate in dependence on the dynamic information contained in a myoelectric signal associated with the onset of muscle contraction.

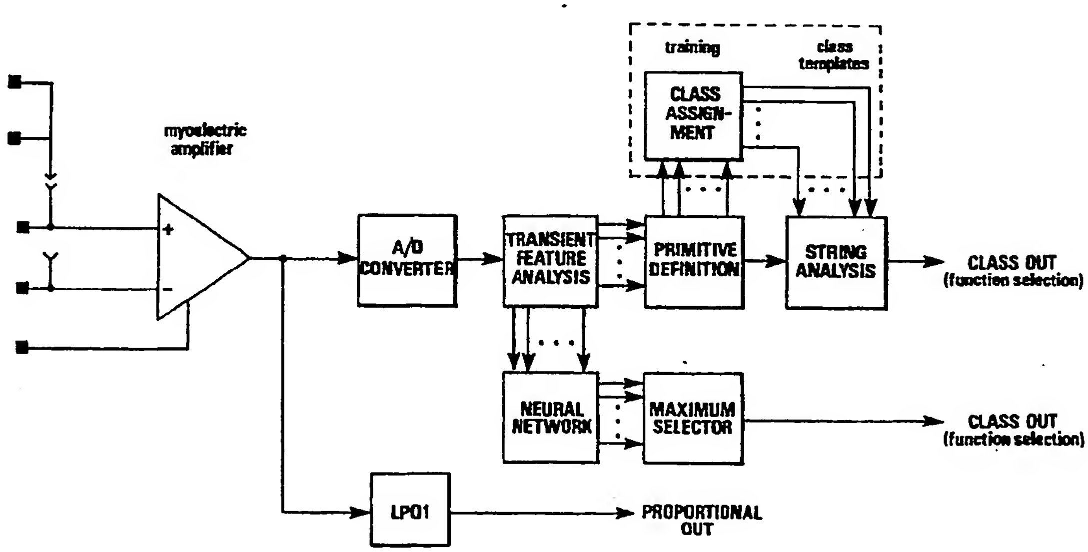

FIG.1.

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it is controlled proportionally using the signal from the low pass output (LP01), and the function continues until LP01 falls below a selected threshold. It is to be understood that inputs to neural network are features from several consecutive segments. Either syntactic analysis or the neural network implementation is chosen for function classification.

In essence, therefore, the new approach illustrated in Figure 1 increases the amount and quality of information used to determine limb function from a single myoelectric channel. In other words, the invention aims to increase the number of functions of an artificial limb which can be controlled by a single myoelectric channel. The novel aspect of this invention is not the classification scheme but rather the use of the dynamic information in the signal to enhance classification. This approach can be used to classify other signals with properties similar to the myoelectric signal. These include myoacoustic and seismic waveforms. Although syntactic analysis has been used to some extent on the latter waveform type there is no mention in the literature of mapping the statistical properties onto a neural network.

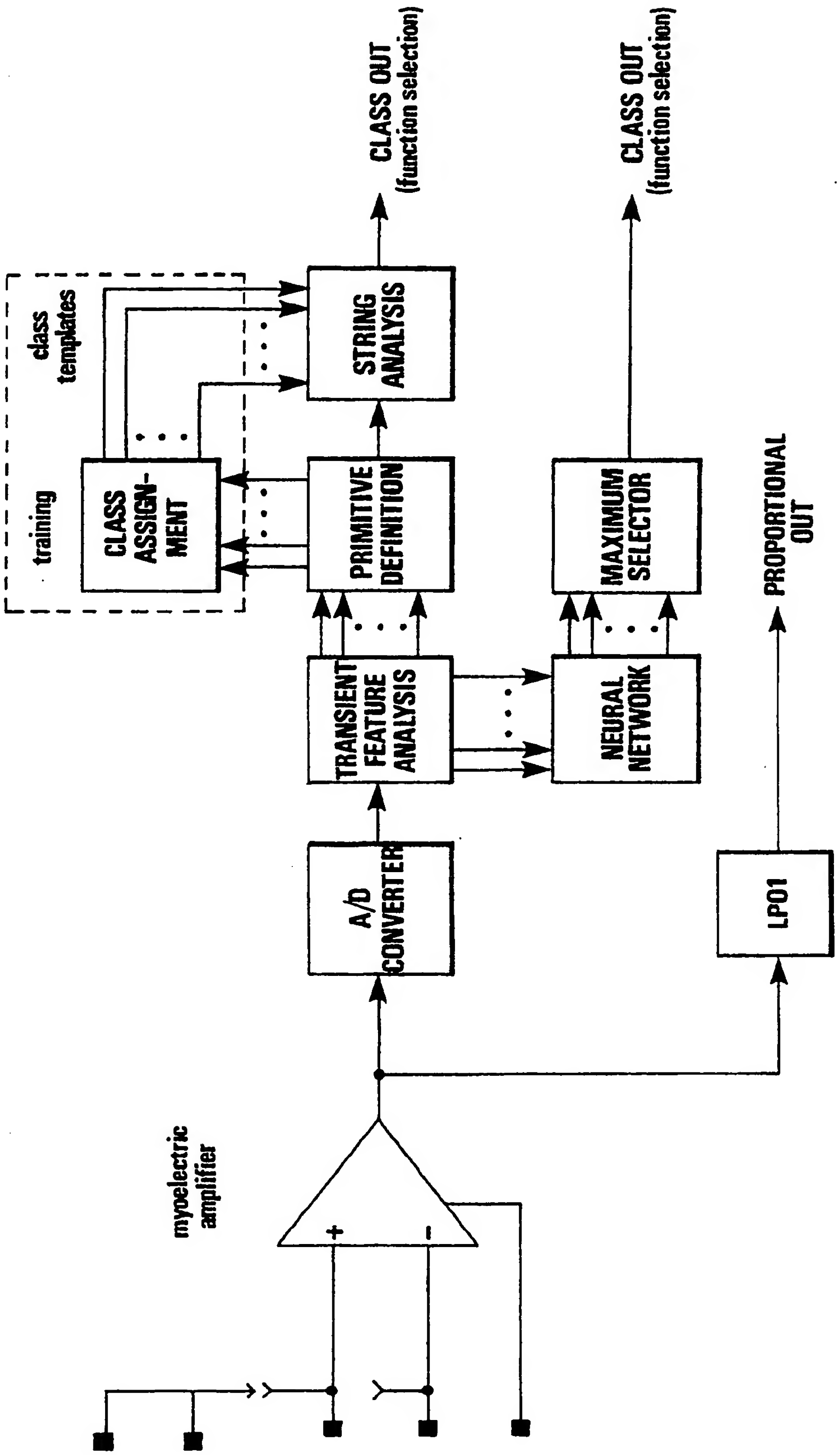
A myoelectric control system based on this approach must be trained to recognize the individual patterns generated by each user. This requires a training period in which the user repetitively generates patterns of known class. The control system uses the parameters extracted from these patterns to define the descriptors for each distinct pattern class. The training period will have to be repeated whenever the limb is put on. Once the descriptors are determined for the pattern classes, retraining can begin with these values. In this way retraining will be much quicker than the original training period. This training, however, does provide the user with the flexibility of using those control contractions which he or she can generate best, and to alter these to redefine the control patterns.

Preliminary experiments have shown that a pattern classification based on the proposed scheme is feasible. A computer implementation resulted in a correct classification rate of over 95% for a 5-state, four- function control system and over 80% for a 7-state, 6-function system. These results were obtained with very little operator training and it is expected that familiarity with the system will give even better results. The experimental system was based on a neural network implementation of the proposed scheme as outlined in the algorithm given below. A scheme based on syntactic analysis of the myoelectric patterns is being implemented. Work is continuing to determine which parameters of the myoelectric patterns give the best classification.

ALGORITHM for the NEW MYOELECTRIC CONTROL SYSTEM

1. Begin system training
-M = 1
(a.)loop 1
-P = 1
-for contraction type M.
(b.)loop 2
-initialize system.
-set N = 1.
-collect 40 samples of myoelectric data.
-check sum:if sum<threshold1 drop oldest sample add next; check sum.
-calculate statistics on those 40 samples, assign to segment N.
-increment N
(c.)loop 3
-collect 40 samples of myoelectric data.
-calculate statistics; assign to segment N.
(d.)if N<desired length loop; increment N; goto-(c.).
(e.)else store segment statistics with associated contraction type M.
(f.)increment P. if P<desired # of training sets goto(b.).
(g.)else increment contraction type M.
(h.)If M< desired number of types go to (a.).
(i.)else train neural network on PxM training sets.
(j.)store weight array calculated during neural network training.
2. Real Time Operation
(a.)initialize system.
-N = 1
(b.)collect 40 samples of myoelectric data.
(c.)check sum:if sum<threshold1 drop oldest sample add next; check sum.
(d.)calculate segment N statistics.
(e.)increment N; if N<desired length goto(b.).
(f.)use segment statistics as input to trained neural network.
(g.)choose maximum output of the neural network as function selector.
(h.)control this function proportionally using level from filtered MES.
(i.)if level<on threshold goto(a.).

Figures 2a to 2d show the dynamic patterns of myoelectric signal which accompanies the onset of muscle contraction. Each Figure comprises 12 graphs illustrating a series of 12 contractions showing the reproducibility of the inherent structure in the myoelectric burst patterns for each contraction type. Figure 2e is a composition of 3 repeats for each of 4 contraction types. It is the unique characteristics extracted from these patterns for contractions which vary in intent, (e.g. elbow flexion, supination, etc.) which determine pattern class. The experimental system extracted zero crossings and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CLASS OUT
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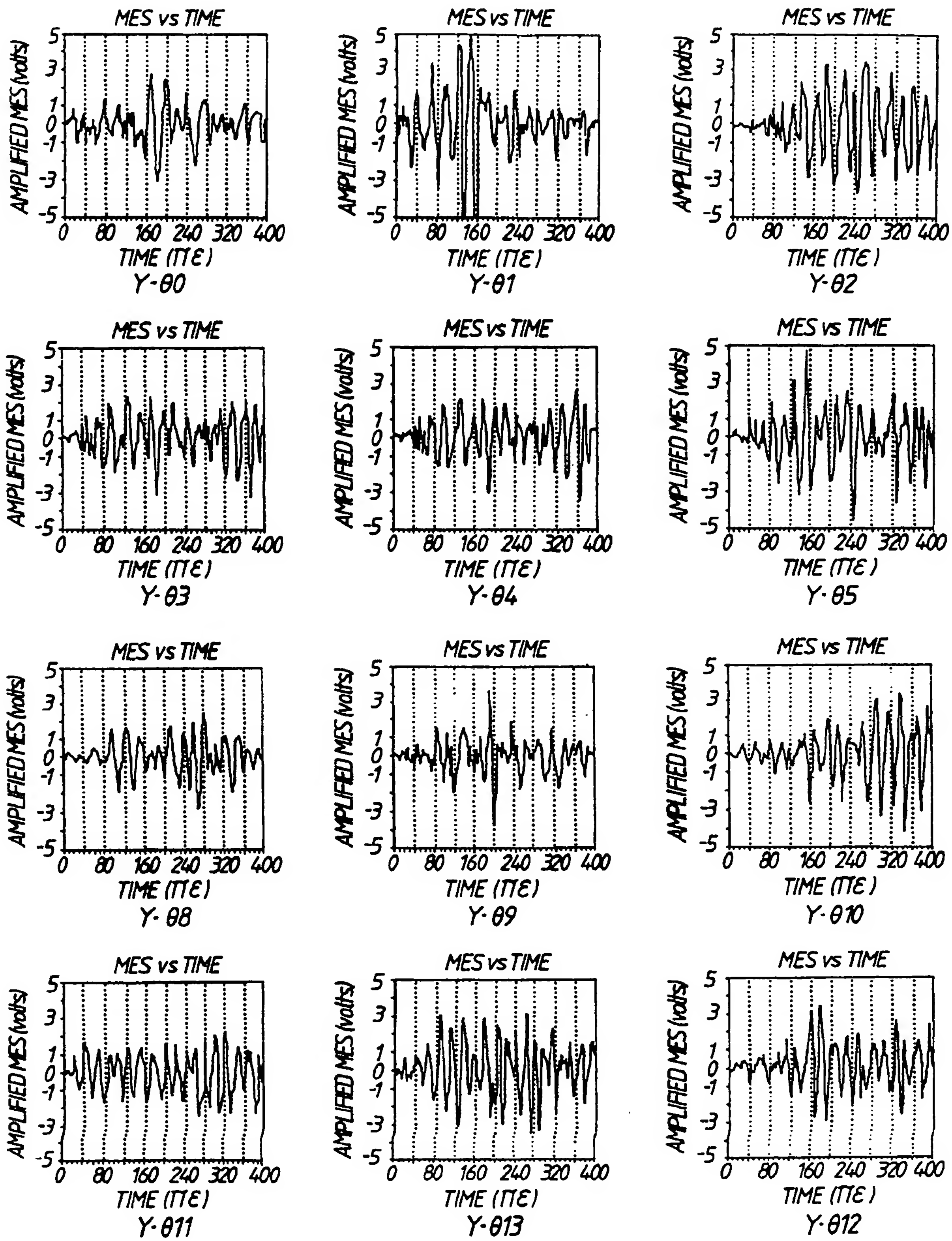
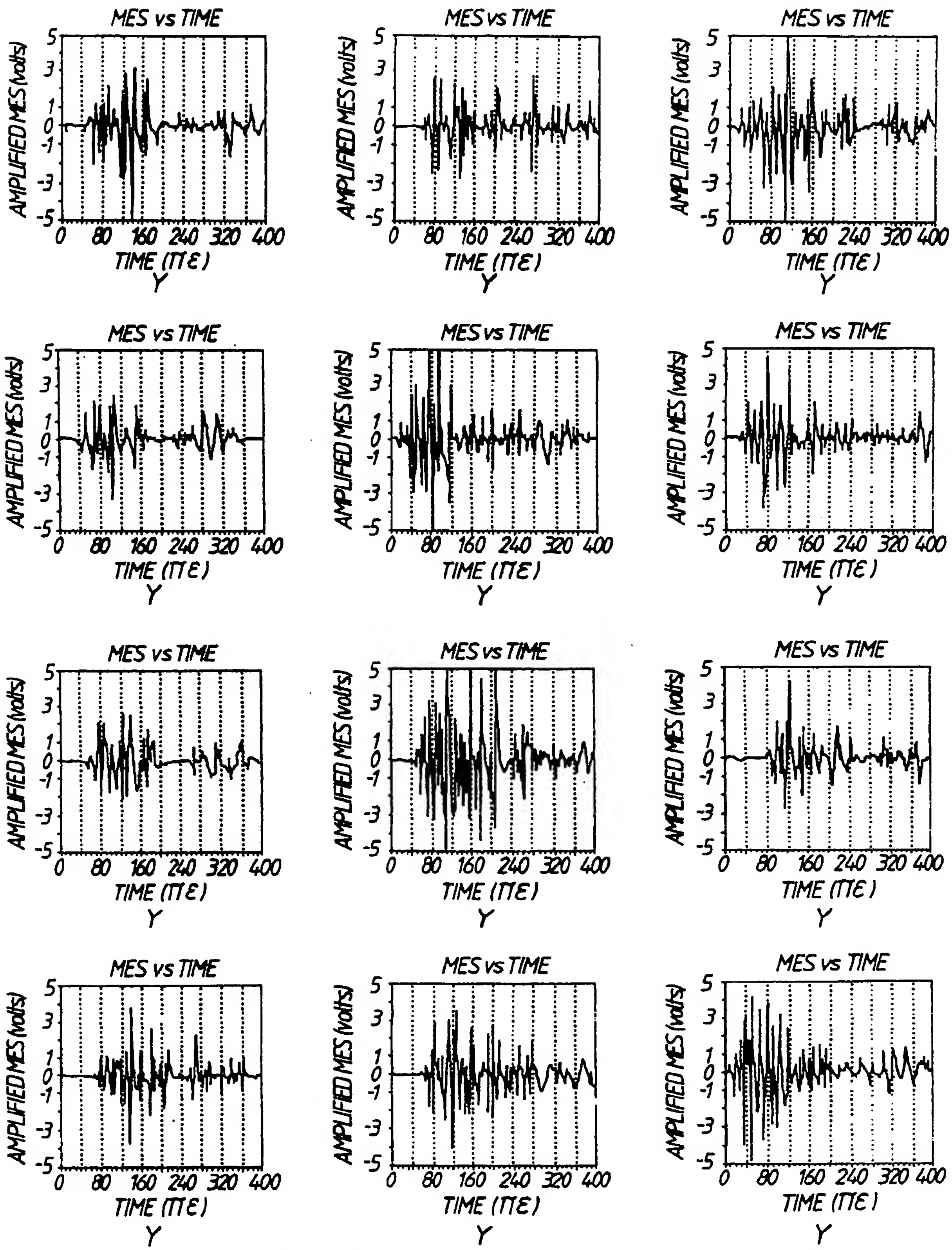
NEURAL
NETWORK
PROPORTIONAL
OUT
A/D
CONVERTER
LP01
myoelectric
amplifier
+
-

FIG.1



Y= CONTRACTION TYPE - ELBOW FLEXION

FIG.2b



Y= CONTRACTION TYPE - PRONATION

FIG.2d